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Estimation of forest Leaf Area Index using remote sensing and GIS data for modelling net primary production

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Abstract. Ecosystem models can be used to estimate *potential net primary production (pNPP)* using GIS data, and remote sensing input of actual forest leaf area to such models can provide estimates of current *actual net primary production (aNPP)*. Comparisons of pNPP and aNPP for a given site or regional landscape can be used to identify forest stands for different management treatments, and may provide new information on wildlife habitat, forest diversity and growth characteristics. Leaf area estimates may be obtained from satellite imagery through correlation with physiologically-based vegetation indices such as the Normalized Difference Vegetation Index (NDVI). However, in areas with high Leaf Area Index (LAI), vegetation indices usually saturate at leaf areas greater than about 4. In predominantly deciduous (hardwood) and mixedwood stands remote sensing estimates may be influenced by understory and other factors. We examined digital Landsat TM imagery and GIS data in the Fundy Model Forest of southeastern New Brunswick to determine relations to forest leaf area index within different stand structures or covertypes. The image data were stratified using GIS covertype information prior to development of LAI predictive equations using spectral reflectance, and the prediction of LAI from Landsat TM imagery was improved with reference to estimates of stem density which are standard forest inventory information contained in GIS databases. Actual stand LAI was compared to assumed maximum LAI values for several species and sites using an ecosystem process model (BIOME-BGC) which relies on climate, soils and topographic information also obtained from the GIS. Subsequent comparison of pNPP and aNPP revealed that even disturbed sites in this environment can reach close to maximum site potential. Specific sites with suboptimal species composition were identified. A future refinement of this approach is to classify the imagery independently of the GIS, which assumes a homogeneous covertype for each polygon in the system, and thus improve still further the aNPP estimates through higher covertype and LAI estimation accuracy.

1. Introduction

Ecosystem models, for example, BIOME-BGC (Running and Hunt 1993) can be used to estimate *potential net primary production (pNPP)* when the necessary information on species, soils, topography and climate are available. Remotely-sensed

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estimates of forest stand attributes such as covertype and leaf area index (LAI) describe the state of a forest at a point in time, and can be input to ecosystem models to estimate current *actual net primary production (aNPP)*. The combination of modelling biospheric processes and remote sensing (Ruimy *et al.* 1994, Milner *et al.* 1996) can be used to derive comparative estimates of the potential productivity or pNPP at that site under the prevailing synoptic and regional conditions, and the actual productivity or aNPP at a given site based on the existing state of vegetation. This comparison of pNPP and aNPP may be used to assess forest health or forest management practice, and represents a new tool and information source for managers in a wide variety of applications including wildlife habitat mapping, biodiversity and forest growth assessment.

Certain forest conditions are problematic in estimation of LAI by conventional remote sensing image analysis of multi-spectral data (Nemani *et al.* 1993, Spanner *et al.* 1994, Peddle *et al.* 1996, Jasinski 1996). For example, spectral vegetation indices such as the normalized difference vegetation index (NDVI) relate to forest LAI, but such relations differ for broadleaf and needleleaf species because of different reflectances in the near-infrared portion of the spectrum. Hardwood and mixedwood stands with variable amounts of understory, and a range of crown covers are very common globally, but are largely ignored in remote sensing studies of LAI which often focus on pure stands of conifers with full crown closure. Attempts to reduce understory contributions have been reported (Nemani *et al.* 1993) using different band combinations including the shortwave infrared channels of the TM sensor. Bonan (1993) found that relations between NDVI and LAI depend on species and stand structure and that covertype variations should be accounted for in subsequent model calculations of photosynthesis and other ecosystem processes. These studies suggest that remote sensing input to ecosystem models can take the form of (*i*) better estimates of forest LAI, and (*ii*) better covertype information or classification of species and stand structure.

We used a combined remote sensing and ecosystem modelling approach to estimate pNPP and aNPP for several stands in a managed forest area in southeastern New Brunswick (figure 1). This area includes many stands with high LAI (greater than 4) and much hardwood and mixedwood forest. In an attempt to increase the accuracy of LAI estimation in this type of forest, two GIS parameters were used to stratify the TM imagery prior to LAI estimation from NDVI: (*i*) forest covertype labels, and (*ii*) stem counts or density estimates per hectare. The specific relations within each covertype between LAI and NDVI were tested to attempt to extend the value of TM-derived NDVI over a larger range of field LAI for this particular mix of species and stands. The main objectives of this research effort are to use remote sensing, ecosystem modelling and the forest inventory GIS database to determine pNPP and aNPP for specific stands and for the regional landscape as a whole as an input to consideration of different forest management strategies and treatments.

In subsequent sections we report on the methods developed for estimating LAI in stand types that have been problematic in the past, and on modelling of pNPP and aNPP for a sample of stands. This paper presents some preliminary results to validate the approach in the structurally-complex temperate hardwood forests of southeastern New Brunswick, and to illustrate some possible applications of this information. The ideas and methods in this paper should find wide applicability since simple forest inventory GIS data, such as that employed in our work, is commonly available for any forest area under active or even passive management

Figure 1. Location of the study area in southeastern New Brunswick, Canada.

planning. In Canada, for example, this includes all national parks and reserves, all timber license areas, virtually any forested environmentally sensitive area, and so on. In fact almost the entire accessible forest land base in this country has been inventoried and mapped to this level of detail over the past ten years, and several provincal or federal resource/mapping units have been involved in compiling this type of ancillary information. Other parts of the world are similarly well documented, if not as well-mapped, and such information is often available in simple GIS database formats. In general, the paper validates an approach and improves on the specific methods in that approach in a new modelling and remote sensing application in a complex, important, mixedwood forest region.

2. Study area

The Fundy Model Forest is a 420 000 ha working forest in southeastern New Brunswick established as part of an international initiative to establish sustainable forest management practices. A combination of Crown Lands, the Fundy National Park, private wood lots and industrial freehold lots, the Fundy Model Forest is composed of a variety of broadleaf deciduous and coniferous species in the Acadian Forest Region (Rowe 1972). The dominant hardwoods are red-maple (*Acer rubrum* L.) and trembling aspen (*Populus tremuloidies* Michx.), with isolated stands of beech (*Fagus grandifolia* Ehrh.), white and yellow birch (*Betula papyrifira* Marsh., and *Betula alleghaniensis* Britton). The dominant softwoods are jack pine (*Pinus banksiana* Lamb.), white pine (*Pinus strobus* L.) and red pine (*Pinus resinosa* Ait.), white spruce (*Picea glauca* (Moench) Voss) and red spruce (*Picea rubens* Sarg.). Mixedwood stands are mainly grouped as intolerant hardwoods (dominated by combinations of aspen and jack pine), and tolerant hardwoods (dominated by red maple, birch, balsam fir (*Abies balsamea* (L. Mill.), and white spruce). The area was heavily glaciated during the last ice maximum, and is underlain by a complex lithological sequence. Local topography is therefore characteristic of the northern Appalachian Mountain root; short, steep slopes and poor drainage patterns with a thick overburden of till and unconsolidated diamicton.

This wide range of species and site conditions has led to a complex classification system used in forest inventory and mapping. A general covertype scheme is used in the GIS database to organize the stands in different strata for consideration of various management treatments (logging, planting, pruning, thinning, suppression, and so on) (see table 1). The main focus of the present study centred on some representative stands in four ecoregions of the Model Forest (figure 2) and 17 plots located north of the town of Sussex (approx. latitude 46° N, longitude 65° W).

3. Data acquisition and methods

Using data from the field, the forest inventory GIS and the TM satellite imagery we derive forest stand LAI within three general GIS covertypes, and we test the influence of these remote sensing estimates of LAI on pNPP and aNPP simulations using BIOME-BGC. In a separate communication (Franklin *et al.* 1996) we have shown the influence of stand covertype variability *within the GIS covertypes* on pNPP and aNPP simulations in a larger sample of stands throughout the model forest area.

3.1. *Field and GIS Data*

Field data consisted of (*i*) a GIS database for the Fundy Model Forest, (*ii*) general timber cruise information on species, density, age, height and site class for a sample

Table 1. GIS covertype labels for the plots in the sample used to generate estimates of LAI from the TM imagery in the Sussex region of New Brunswick.

Class label		Dominant species or mix
Hardwoods		
TH	Tolerant Hardwoods	Maple, Beech, Birch
IH	Intolerant Hardwoods	Aspen
MH	Mixed Hardwoods	All deciduous species
Softwoods		
Sp		Spruce
Bf		Balsam Fir
Jp		Jack Pine
MC		All conifer species
Mixedwood (examples)		
SpTH		Spruce-Tolerant Hardwoods
SpIH		Spruce-Intolerant Hardwoods
THSp		Tolerant Hardwoods-Spruce
IHSp		Intolerant Hardwoods-Spruce
JpTH		Pine-Tolerant Hardwoods
JpIH		Pine-Intolerant Hardwoods
THJp		Tolerant Hardwoods-Pine
IHjP		Intolerant Hardwoods-Pine
BfTH		Fir-Tolerant Hardwoods
BfIH		Fir-Intolerant Hardwoods
THBf		Tolerant Hardwoods-Fir
IHBf		Intolerant Hardwoods-Fir

of 128 stands, and (*iii*) detailed plot-level information at 17 locations where destructive sampling was used to develop allometric relationships to leaf area index for commercially-important species, and to other structural features such as branch biomass (Lavigne, unpublished, Lavigne *et al.* 1996). At each 20 m by 20 m plot four quadrants were measured and surveyed and the centre located precisely with a differentially-corrected Trimble Navstar GPS unit.

The GIS data consisted of soils units, forest cover types, ecoregion boundaries and digital elevation data. The forest cover type information was derived from aerial photointerpretation work which included separation of some of the main covertypes: stands dominated by tolerant hardwoods, intolerant hardwoods, spruce, pine and fir, and a wide range of mixedwood combinations of species and structures. The ecoregion boundaries are defined with climatic information from the stations noted on figure 2. The digital elevation model data were used to estimate slope and aspect for each of the plots and for each stand in the database.

3.2. *Remote sensing data*

The Landsat TM imagery were acquired on 7 August 1992, geometrically corrected to the UTM projection with less than 0·5 pixel rms error at 20 ground control points, and atmospherically-adjusted using the dark-pixel subtraction method (Franklin and Giles 1995). An analysis of spectral/forest relations was conducted using regression between field LAI, aerial remote sensing data and the TM-derived NDVI values at each of the 17 plot locations (Wulder *et al.* 1996). The NDVI values were computed for each quadrant surveyed on the ground using a single TM pixel

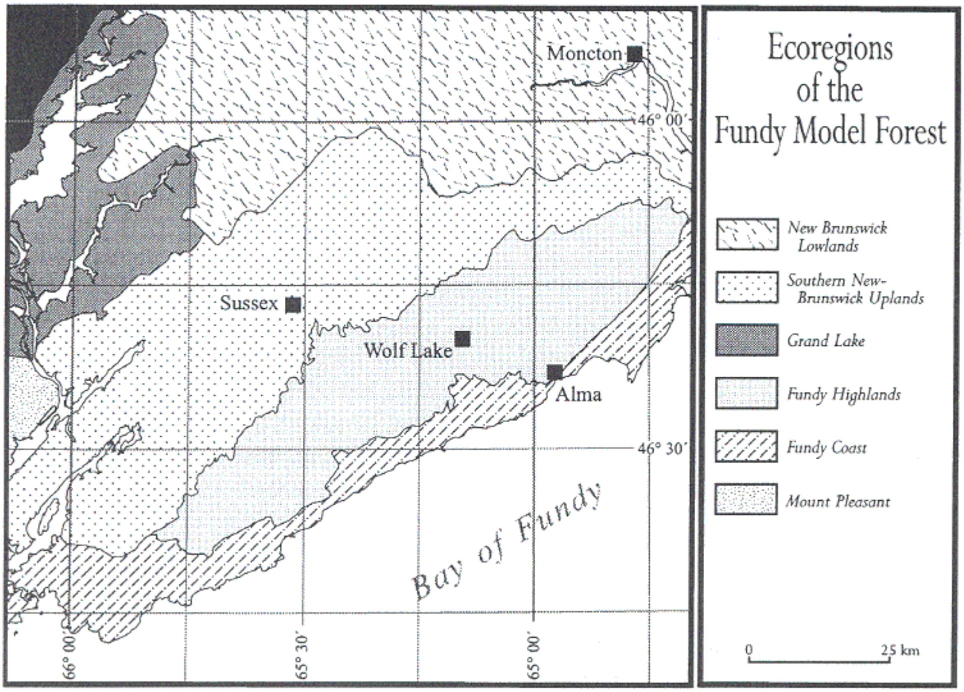

Figure 2. The location of the climate stations used to represent four ecoregions within the Fundy Model Forest.

at that geometric location. A mean NDVI using 3 by 3 and 5 by 5 TM pixel windows was tested as a way to reduce the possible influence of the geometric error and the chance variability due to the location of the centre pixel (Ahern *et al.* 1991); however, no differences in results were found compared to the single pixel analysis.

3.3. *Modelling input*

BIOME-BGC (figure 3) is a mechanistic ecosystem model derived from an earlier conifer forest ecosystem model, but now designed to generalize ecosystem biogeochemical and hydrological cycles across a wide range of climate and lifeforms (Running and Hunt 1993). The model requires site data which were available in the GIS data layers for each ecoregion. The GIS soil data layer provided estimates of soil texture, depth and coarse fragment content for soil water holding capacity estimates.

We examined several years of climate data from stations in four ecoregions (Alma on the Fundy Coast, Wolf Lake in the Fundy Highlands, Sussex in the Southern Uplands, and Moncton in the New Brunswick Lowlands, see figure 2), and selected the year 1981 as typical of weather in the region because the monthly precipitation (figure 4), mean maximum air temperature and mean minimum air temperature were closest to the mean for the period of record for all four stations. A preliminary model run on a tolerant hardwood stand showed the substantial differences in forest productivity as a result of differences in climate and soils (figure 5).

To test differences in productivity which result from differences in LAI, BIOME-BGC was run on each of the 17 forest plots using actual LAI values estimated from field data, the TM imagery, and also using maximum LAI values predicted by the model for each stand based on physiological assumptions for that climate and soil type (Hunt and Running 1992). Areas of differences in these estimates can be used to validate the model and the remote sensing inputs, and may also translate into different NPP estimates (pNPP versus aNPP) which may be used to test different management treatments within the context of a managed ecosystem.

4. Results and analysis

Overall the relation between LAI and NDVI across all sampled covertypes in the 17 plots was weak but statistically significant (table 2). The regression coefficient was 0·15. This is a weaker relationship between LAI and NDVI than that described by Franklin and Luther (1995) in a simpler, (structurally) monospecies forest in Newfoundland. They reported an R-squared value of 0·29 and a standard error of 2·31 in LAI prediction for 36 stands dominated by balsam fir. In Oregon, Spanner *et al.* (1994) report higher correlation coefficients but similar standard errors in a similar wide range of forest conditions (species and structure) for a variety of sensors. However, it is clear that the overall relation between LAI and NDVI is weak and not substantively useful across the New Brunswick stand types and species combinations.

The 17 plot locations were grouped into softwood, hardwood and mixedwood covertypes to stratify the analysis of relations between LAI and remotely-sensed data. The NDVI calculated from the TM data was highly correlated to LAI in softwood stands, but much less correlated in hardwood and mixedwood stands (table 2). Our regression coefficient (0·93) for conifer stands was similar to that observed by Chen and Cihlar (1996) and much better than that found in the earlier work in Newfoundland which included a wider range of stand age, density and growth characteristics (Franklin and Luther 1995). The lower correlations for hardwood

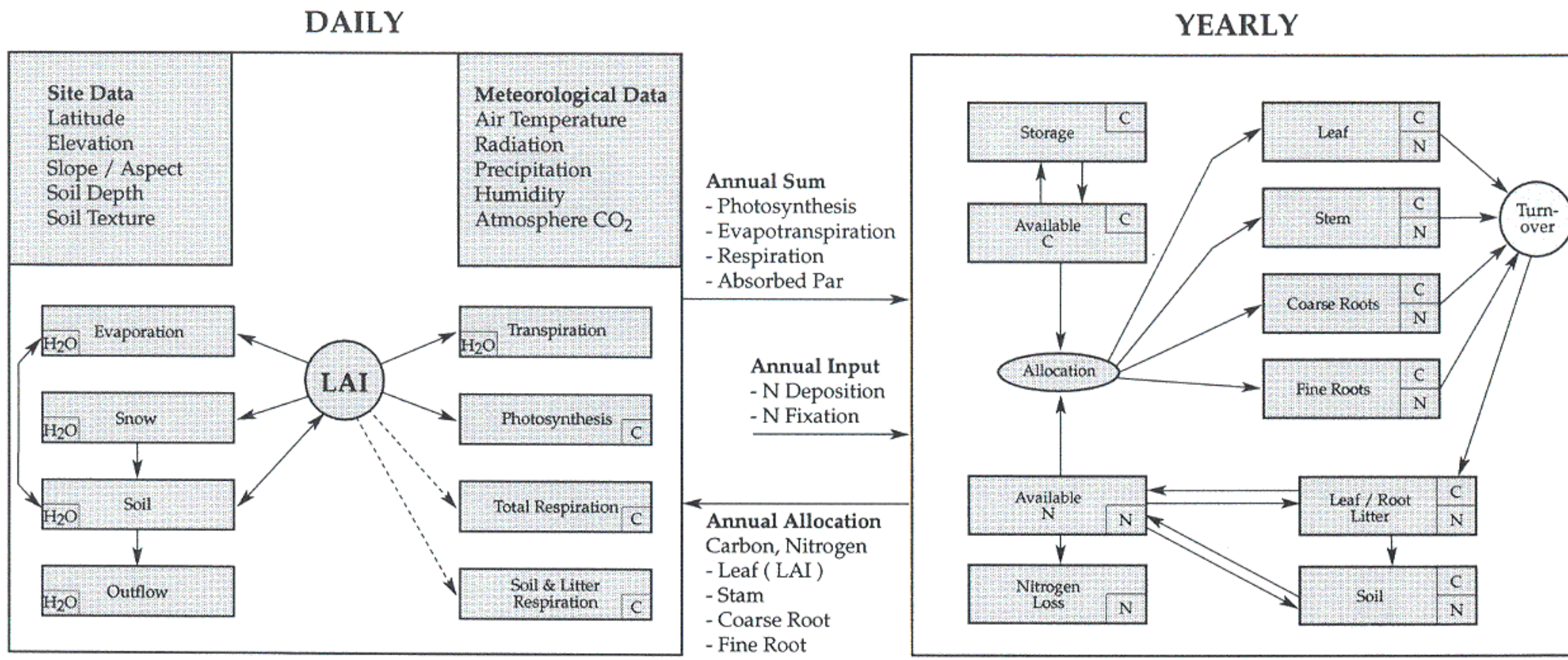

Figure 3. Flowchart for BIOME-BGC ecosystem process model. The model simulates the biogeochemical cycles of carbon, water and nitrogen; the boxes show current amounts and the arrows between the boxes show the fluxes. LAI controls the rates of daily fluxes directly (solid arrow) and indirectly (dotted arrow). Allocation and turnover control the annual fluxes.

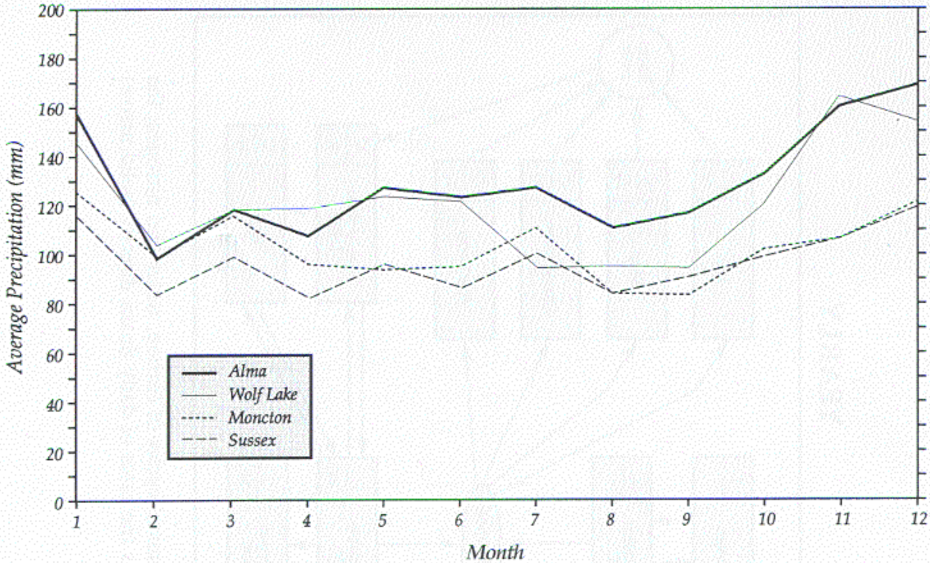

Figure 4. Monthly average precipitation in a representative year (1981) for the four climate stations used in modelling potential productivity by ecoregion.

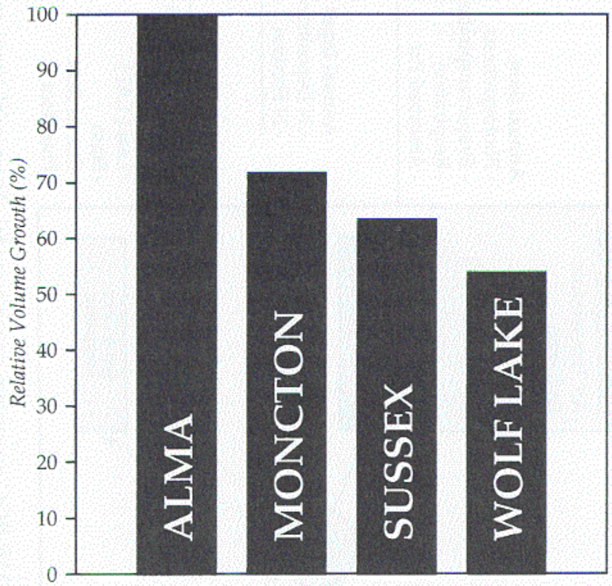

Figure 5. BIOME-BGC estimates of relative potential productivity of a tolerant hardwood stand for four ecoregions based on climate, soils and topographic data.

and mixedwood stands illustrate the difficulty in LAI estimation by remote sensing. There are specific differences in leaf thickness, shape and distribution within crowns that influence reflectance and there may be differences among covertypes in stand structure, for instance in the amount of understory vegetation, that also influence LAI : NDVI relations.

Multiple linear regressions using stem density and NDVI substantially improved correlations with LAI for hardwood and mixedwood stands for the measured plots in comparison to the simple correlations (table 2). These results suggest that LAI might be accurately estimated for large areas with TM data by using forest inventory data to (*i*) stratify by covertype, and (*ii*) provide estimates of stem density. For example, Spanner *et al.* (1990) found that estimates of LAI improved in areas where crown closure was greater than 90 per cent compared to areas with more open canopies, less dense stocking and with understory exposed to the sensor.

Over the larger sample of 128 stands differences in LAI estimation based on the field measurement of sapwood, the remote sensing vegetation index, and the ecosystem model are significant (figure 6). For example, in the softwood stands the mean LAI was 10·48 based on the measured sapwood allometric equation, but 11·10 using the LAI/NDVI relation. The model assumption of maximum LAI for these sites based on soils and climate was 7·5. Although the softwood LAI estimates are reasonably comparable, it appears that the remotely-sensed LAI in stands with significant deciduous species is underestimated relative to the field measurements. Actual LAI is higher than modelled LAI for most sites with the exception of the mixedwood stands.

Table 3 shows the difference between pNPP, which is calculated based on the assumption of a maximum LAI for each site (based on climate and soils), and aNPP which is calculated using the actual LAI derived from the Landsat imagery for each site based on the GIS covertype label. In the model, the aspen and spruce parameters are from Hunt and Running (1992). The simulations are for the Sussex climate station on the Harcourt soil unit (red-mudstone, weathered compact till, sandy loam) which represents some of the best sites in the region. Overall, the Model Forest

Table 2. *R*-squared values between field measurements of LAI and TM-derived NDVI values, with and without GIS database estimates of tree density (stem counts) within three dominant covertypes.

	LAI	Stems	$R^2_{TM+Stems}$
Softwood plots			
Mean LAI = 4·51			*0·98*
Stems	0·05		
TM	0·93	0·05	
Hardwood plots			
Mean LAI = 4·93			*0·25*
Stems	0·10		
TM	0·13	0·04	
Mixedwood plots			
Mean LAI = 5·28			*0·82*
Stems	0·67		
TM	0·66	0·47	
Overall			
Mean LAI = 4·90			*0·28*
Stems	0·12		
TM	0·15	0·07	

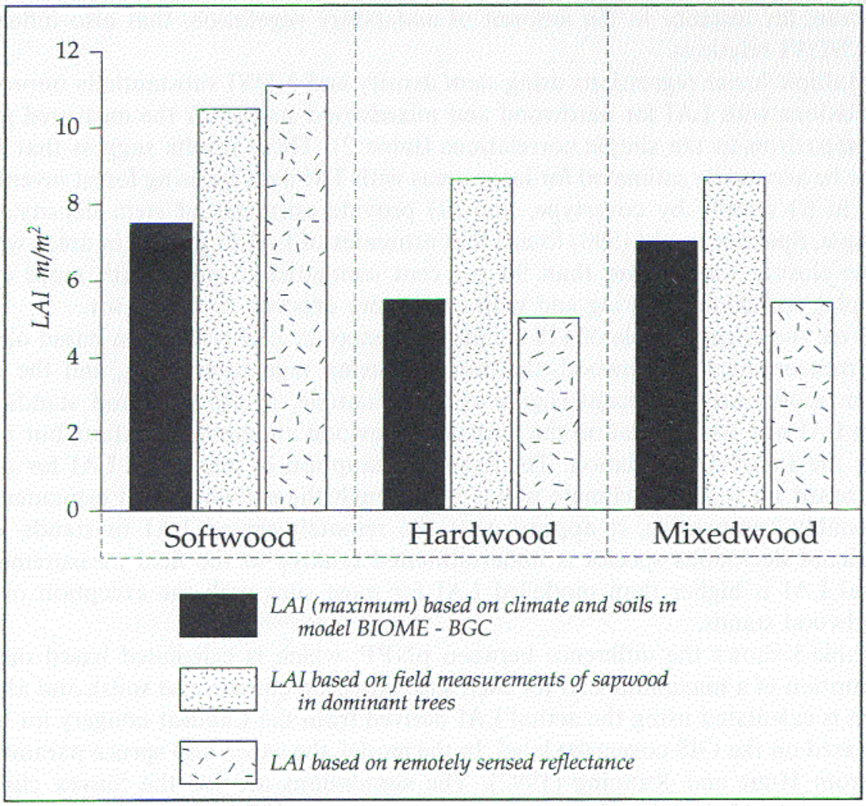

Figure 6. Comparison of field-based, remotely sensed and modelled LAI for a sample of 128 stands in three general covertypes.

Table 3. Example pNPP and aNPP estimates simulated with BIOME-BGC for plots grouped by covertypes in the GIS database and using assumed LAI values (maximum) and calculated LAI values (TM-derived NDVI plus density estimates).

Plot type	LAI_{max}	pNPP*	LAI_{TM}	aNPP*
Softwood	7·5	10·0	5·7	9·5
Aspen	5·0	18·6	4·7	17·4
Maple	6·0	17·9	4·5	13·1
Mixedwood	7·0	18·5	6·3	16·0

* Mg carbon ha^{-1} $year^{-1}$.

stand productivity appears to be relatively close to the maximum in all types except the tolerant hardwoods (maple), where the aNPP is approximately 75 per cent of the pNPP on all sites. A more precise, spatial analysis of areas that are well below productivity reveals covertypes and individual stands which can be considered for different management treatments. For example, in the 17 plots for this study (table 4), simulations show that aNPP is consistently below pNPP in the jack pine plantations, and also as expected in the tolerant hardwood plots. In the two jack pine plantations actual productivity averages only about 60 per cent of the potential

Table 4. Individual plot NPP estimates simulated with BIOME-BGC using assumed LAI values (maximum) and calculated LAI values (TM-derived NDVI plus density estimates).

Plot	GIS label	dbh cm	stem C MgC ha	LAI	LAI max	aNPP	pNPP	%max
ds2	Jp	12·12	72·1	5·5	7·5	7·8	10·2	76·4
ds3	Sp	16·5	157·7	5·86	7·5	7·4	9·6	77·0
ds5	TH	12·96	110·5	5·35	6	7·2	7·8	92·3
ds6	BfTH	19·96	164·3	4·92	7	6·6	8·4	78·5
ds7	TH	18·32	131·8	5·28	6	7·2	7·8	92·3
ds8	THSp	15·16	124·1	5·82	7	6·8	7·2	94·4
ds9	TH	16·31	70·5	4·03	6	7·6	9·6	79·1
ds10	H	14·86	110·6	4·82	5	8	8·2	97·5
hb1	Jp	5·70	33·6	2·63	7·5	4·8	12·2	39·3
hb3	SpTH	17·37	109·6	4·09	7	5·6	7·6	73·6
hb4	SpTH	14·07	104·9	6·65	7	7·4	7·6	97·3
hb5	TH	15·57	123·8	4·52	6	6·8	7·8	87·1
hb6	TH	16·22	131·7	4·71	6	6·6	7·8	84·6
hb7	SpTH	17·22	61·1	4·25	7	7·4	8·8	84·0
hb8	TH	16·42	108·5	5·14	6	7·2	7·8	92·3
hb9	BfTH	19·39	92·3	4·11	7	7·6	7·6	100
hb10	JpTH	14·52	151·1	6·45	7	6·8	7	97·1

productivity as estimated by the model because of the reduced LAI compared to the maximum LAI for these sites. One possible interpretation of these differences in aNPP and pNPP is that jack pine is not an appropriate species for these two sites as it cannot take advantage of the water and nutrients that are available.

Overall, however, the estimates of LAI (and subsequently aNPP) are surprisingly close to the maximum LAI and pNPP. While this appears to validate the model and the approach used in this study, this also might suggest that even disturbed stands in this part of the world can have forest LAI close to the maximum site potential based on soils, climate and topography. On the other hand, if these trends were extended over the entire area of the Model Forest (assuming that these results are generally applicable) such differences in actual and potential productivity represent a significant amount of lost production, particularly in areas with poorer soils and harsher climates.

5. Conclusion

We obtained more precise LAI estimates from Landsat TM satellite imagery by using GIS covertype labels and stem density estimates to stratify the sample and derive different predictive equations for three general classes of stands. Estimates of LAI using this approach were much improved in hardwood and mixedwood stands in comparison to estimates obtained by conventional methods of using only one vegetation index (NDVI) calculated from the satellite image. It was feasible to make realistic estimates of aNPP using BIOME-BGC for coniferous (softwood), deciduous (hardwood) and mixedwood stands with our remote sensing estimates of LAI. Because the requisite soils, topography and climatic data were available we also estimated maximum LAI and pNPP using the ecosystem model BIOME-BGC. The estimates of aNPP were compared to those of pNPP to illustrate some applications of this approach, including detection of two plantations operating significantly below potential because of species incompatibility with site conditions. Overall these preliminary results indicate that disturbed sites in these temperate hardwood forests can have LAI close to maximum site potential, and that other factors such as soil quality and water holding capacity and nutrient fluxes may be limiting productivity.

In summary, this paper is based on the integration of remote sensing, GIS and ecosystem modelling ideas and results that improve the methods which can lead to assessment of productivity in forest ecosystems at regional and local scales, based on:

(*a*) A comparison aNPP and pNPP for individual stands in a complex, mixedwood, northern forest with extension to the regional landscape as a whole.
(*b*) Stratifying the forest samples by forest covertype prior to estimation of the NDVI : LAI relation.
(*c*) The use of GIS data (density or stem count estimates) to increase the accuracy of the LAI estimates.

Acknowledgments

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References

Ahern, F., Erdle, T., MacLean, D. A., and Kneppeck, I. D., 1991, A quantitative relationship between Landsat TM spectral response and forest growth rates. *International Journal of Remote Sensing*, **12,** 387–400.

Bonan, G., 1993, Importance of LAI and forest type when estimating photosynthesis in boreal forests. *Remote Sensing of Environment*, **43,** 303–314.

Chen, J., and Cihlar, J., 1996, Retrieving leaf area index of boreal conifer forests using Landsat TM images. *Remote Sensing of Environment*, **55,** 153–162.

Franklin, S. E., and Giles, P. T., 1995, Radiometric processing of aerial and satellite remote sensing imagery. *Computers & Geosciences*, **21,** 413–425.

Franklin, S. E., and Luther, J. E., 1995, Satellite remote sensing of balsam fir forest structure, growth and cumulative defoliation. *Canadian Journal of Remote Sensing*, **21,** 400–411.

Franklin, S. E., Wulder, M. A., Lavigne, M. B., Deuling, M. J., and Hunt, E. R. jr, 1996, Classification of forest covertype for use in ecosystem models of net primary production, *Canadian Journal of Remote Sensing*, submitted and in review.

Hunt, E. R., and Running, S., 1992, Simulated dry matter yields for aspen and spruce stands in the North American boreal forest. *Canadian Journal of Remote Sensing*, **18,** 126–133.

Jasinski, M., 1996, Estimation of subpixel vegetation density of natural regions using satellite multispectral imagery. *I.E.E.E. Transactions on Geoscience and Remote Sensing*, **34,** 804–813.

Lavigne, M., Luther, J. E., Franklin, S. E., and Hunt, E. R., jr, 1996, Comparing branch biomass prediction equations for *Abies balsamea*. *Canadian Journal of Forest Research*, **26,** 611–616.

Milner, K., Running, S. W., and Coble, D. W., 1996, A biophysical soil-site model for estimating potential productivity of forested landscape. *Canadian Journal of Forest Research*, **26,** 1174–1186.

Nemani, R., Pierce, L., Running, S., and Band, L., 1993, Forest ecosystem processes at the watershed scale: sensitivity to remotely-sensed Leaf Area Index estimates. *International Journal of Remote Sensing*, **14,** 2519–2534.

Peddle, D., Hall, F. G., and LeDrew, E. F., 1996, Remote sensing of boreal forest biophysical variables using spectral mixture analysis and a canopy reflectance model. *Proceedings of the 18th Canadian Symposium on Remote Sensing: Vancouver, BC*, (Ottawa: Canadian Aeronautics and Space Institute), pp. 418–421.

Rowe, J. S., 1972, Forest regions of Canada. Environment Canada, Canadian Forest Service Publication No. 1300 (Ottawa, Ontario: Environment Canada).

RUIMY, A., SAUGIER, B., and DEDIEU, G., 1994, Methodology for the estimation of net primary production from remotely sensed data. *Journal of Geophysical Research*, **99,** 5263–5283.

RUNNING, S., and HUNT, E. R., JR., 1993, Generalization of a forest ecosystem process model for other biomes, BIOME-BGC, and an application for global-scale models. In *Scaling Physiological Processes: Leaf to Globe* (New York: Academic Press) pp. 141–157.

SPANNER, M. L., PIERCE, L., PETERSON, D., and RUNNING, S. W., 1990, Remote sensing of temperate coniferous forest leaf area index: the influence of canopy closure, understory vegetation and background reflectance. *International Journal of Remote Sensing*, **11,** 95–111.

SPANNER, M., JOHNSON, L., MILLER, J., MCCREIGHT, R., FREMANTLE, J., RUNYON, J., and GONG, P., 1994, Remote sensing of leaf area index across the Oregon Transect. *Ecological Applications*, **4,** 258–271.

WULDER, M., FRANKLIN, S. E., and LAVIGNE, M. B., 1996, Statistical texture properties of forest structure for improved LAI estimates from CASI. *Proceedings of the 18th Canadian Symposium on Remote Sensing: Vancouver, B.C.* (Ottawa: Canadian Aeronautics and Space Institute), pp. 161–164.